

Comparison between different 1RM prediction tests in submaximal load for the usage of a future smartwatch app

Fulfillment of the requirements for the
«Master of Science in Sports with Specialization in Teaching»

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Bern, January 2019

Acknowledgement

This master thesis was conducted at the Institute of Sport and Human Movements Sciences at the University of Fribourg in cooperation with the Swiss Federal Institute of Sports Magglingen and supervised by PD Dr. Lorenzetti Silvio. Hereby, I would like to thank him for his exceptional help when it came to his great advice, his quick responses to my questions and for always showing me the right direction whenever I needed it.

I would also like to thank my advisor Fabian Lüthy for supporting me with good references and helping me when I needed some extra guidance.

Furthermore, I would like to thank Dominik Huber which took his precious time to explain the process of his master thesis to me in depth and showing me how the app and the smart-watch worked. He was always just a phone call away for some really good advice.

I would also like to word my appreciation to Ravi Sinnathamby, Niklaus Jud and Marielle Kunz for letting me use their gym facility and equipment and helping me find suitable test subjects.

Similarly important for the final touch of this thesis were Dr. Samuel Iff, Samuel Böringer, Pascal Stegmann and Cherelle Oestringer for proofreading my thesis, helping with statistical questions and giving me constructive feedback.

Finally, I must also express my very profound gratitude to my parents and siblings for always giving me the needed motivation, support and encouragement throughout this project. I would not have accomplished this thesis, without their help and support.

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Abstract

Overview

Research has shown that there is a fundamental importance of quantification of the maximum load that can be lifted through a full range of motion, when it comes to the design of resistance training programs. Furthermore, workout assistants that can track your resistance training through wrist worn devices have shown to be quite accurate when it came to exercise recognition and repetition counting but needed improvement on the integration of a one repetition maximum (1RM) estimation.

Research Question

The primary aim for this master thesis was to find out which parameters of the load-velocity or reps-to-fatigue relationship formula showed the best accuracy for the 1RM estimation of the exercises barbell bench press, barbell back squat and barbell deadlift. The secondary aim focused on validating the accuracy of a previously developed strength training app and on its functions of exercise recognition, repetition counting and 1RM estimation.

Methods

A subject group consisting of recreationally trained athletes ($N = 30$) performed 4 sets of up to 10 repetitions with an increasing submaximal load (60 – 80 % of predicted 1RM) for each exercise, wearing an Apple watch with an integrated strength training app and having the GymAware Power Tool attached to the bar to collect data.

Results

The adapted formula of Jovanović and Flanagan (2014) and Epley (1985) showed the best correlations in all three exercises. Regarding the app's functions, there was an 88.4 % overall correct exercise recognition and an insignificant correlation ($p = 0.06$) between the true and the recognized repetition counting.

Conclusion

The adapted velocity parameters V_{Peak} and MVT used by Jovanović and Flanagan (2014) showed the best relationship compared to Epley's (1985) formula and, therefore, propose to be integrated into the strength training app. Moreover, the application showed high accuracy with the exercise recognition and decently reliable results with the repetition counting. Future work has to be put into improving the detection of weight displacement of the Apple Watch and the overall user experience.

1 Introduction

In the 21st century chronic diseases, such as the four main non-communicable diseases (NCDs), namely cardiovascular diseases, cancer, respiratory diseases and diabetes, are epidemic worldwide (World Health Organization, 2018). Even children are now more than ever suffering from obesity, diabetes and metabolic syndromes (Federal Office of Public Health (FOPH), 2016; Robert Koch-institut, 2018; World Health Organization, 2017). Furthermore, the World Health Organization (WHO) even stated that «physical inactivity, now recognized as an increasingly important determinant of health, is the result of a progressive shift of lifestyle towards more sedentary patterns» (World Health Organization, 2003, p. 6). The WHO also noted that, even though, the global risk of «dying from any one of the four main NCDs between ages 30 and 70 decreases from 22 % in 2000 to 18 % in 2016» (World Health Organization, 2018, p. 7), an acceleration of progress towards reducing key risk factors is required, in order to meet the 2015 adopted Sustainable Development Goals (SDG) number 3: *Good Health and Well-being*. Even in Switzerland the four main NCDs cancer (women 45.1 %, men 29.3 %), cardiovascular diseases (women 10.5 %, men 16.6 %), chronic respiratory diseases (women 3.2 %, men 2.8 %) and diabetes (women 0.9 %, men 1.2 %) accounted for two-thirds of all deaths (Federal Office of Public Health (FOPH), 2016) and for 80 % of healthcare costs (CHF 700 billion in 2013). It is also reported in the 2015 National Health Report (Schweizerisches Gesundheitsobservatorium, 2015), that some 2.2 million people suffer from a NCD, which include cancer, heart attacks and strokes (cardiovascular diseases), asthma and chronic obstructive lung disease (chronic respiratory diseases), diabetes and disorders of the musculoskeletal system (e.g., osteoarthritis, arthritis, osteoporosis, soft tissue rheumatism and back complaints). The later ones are mostly «influenced by lifestyle: overweight, a lack of physical activity, as well as poor diet, excessive alcohol consumption, smoking and stress» (Federal Office of Public Health (FOPH), 2016, p. 6). A variety of sources have documented a mitigation of progression and even a reversion of existing chronic diseases through physical activity and diet interventions (Roberts & Barnard, 2005). Physical activities can contribute to weight loss, through the creation of a negative energy balance (Alexander, 2002), which is the result when energy intake is lower than energy expenditure. Aerobic exercises that enhance respiratory and circulatory efficiency have a bigger impact on direct caloric expenditure compared to resistance training (Alexander, 2002). Nevertheless, the effects of resistance training towards increasing fat-free mass that results in the increase of the resting metabolic rate (RMR) is just as important, as RMR accounts of about 70 % of daily energy expenditure (American College of Sports Medicine, 2017). This means that on the long run, increasing your muscle mass through resistance training shows to be highly benefi-

cial when it comes to boosting your energy output. Furthermore, it is also important to note that resistance training does not just promote muscular hypertrophy but shows great welfare for general health (Federal Office of Public Health (FOPH), 2016), if it is implemented and executed correctly.

Resistance training has to be properly introduced, individually adapted to the people's need and, therefore, conducted by a fitness instructor, a personal trainer or a workout assistant device. On the one hand, fitness instructors mostly do not have the time nor the knowledge to thoroughly track and individualize the intensity of every workout. On the other hand, personal trainers are very expensive and, hence, are not the best solution for the broader and general public. This brings us to the importance of workout assistant devices, that can track your physical activities through Human Activity Recognition (HAR).

HAR has been the ever-increasing focus of many research studies in the last 20 years (Bulling, Blanke, & Schiele, 2014), due to the raised interest in proactively assisting users in their activities. Their usage has gone from originally being developed for the entertainment sector (Nintendo Wii, Microsoft Kinect) (Crouter, Flynn, & Bassett, 2015; Velloso, Bulling, Gellersen, Ugulino, & Fuks, 2013) to having found further use in the industrial sector (SKODA production facilities) (Maurtua, Kirisci, Stiefmeier, Sbodio, & Witt, 2007), office scenarios and in the fields of fitness and rehabilitation (Kunze et al., 2006; Ladha, Hammerla, Olivier, & Plötz, 2013; Minnen, Westeyn, Starner, Ward, & Lukowicz, 2006). Wrist-worn systems have been developed and tested to automatically recognize physical activities. With the help of accelerometers, global positioning system (GPS) trackers and heart rate / pulse recognition many wrist-worn systems can be used for repetitive aerobic exercises such as walking and running (Troost, Zheng, & Wong, 2014) and have already been successfully introduced to the market (Pernek, Kurillo, Stiglic, & Bajcsy, 2015). But when it comes to tracking resistance training with ubiquitous wrist-worn devices further investigations are still needed (Bleser et al., 2015).

Recently a new strength training iOS app called *Strength Control* for the Apple Watch and iPhone has been developed (Huber, 2017). This project was conducted due to the need of a wrist-worn system that can monitor and recognize human activities in strength training and not having to buy an additional tool for that recognition. But also due to the increasing interest in smartphones (Kranz et al., 2013; Shoaib, Bosch, Incel, Scholten, & Havinga, 2014) and smartwatches (Shoaib, Bosch, Incel, Scholten, & Havinga, 2016) that now have integrated inertial sensor types (accelerometers and gyroscopes) and fast increasing computational power (Incel, Kose, & Ersoy, 2013). With an implementation of motion recognition algorithms, repetition counting and a 1 repetition maximum (1RM) calculation in an iOS app that can be

used on the Apple Watch, workout tracking can be made available to a broader spectrum of athletes and fitness professionals. This shows the overall importance of further researching the topic of 1RM, which Huber (2017) has already mentioned needs further investigation.

1.1 1RM predictions

Research has shown that there is a fundamental importance of quantification of the maximum load that can be lifted through a full range of motion when it comes to the design of resistance training programs (Fleck & Kraemer, 2014; Sayers, Schlaeppli, Hitz, & Lorenzetti, 2018). Maximum load can be seen as an indicator for strength, which forms together with muscular size and power the three main effects of resistance training. There are numerous acute training variables that have been identified and utilized for resistance training program designs, such as exercise type and order, intensity or load, number of repetitions and reps, and rests between sets (Jovanović & Flanagan, 2014), number of exercise interventions, duration of the experimental period, fractional and temporal distribution of the contraction modes per repetition and duration, time under tension, volitional muscular failure and recovery time in-between exercise sessions (Toigo & Boutellier, 2006). The magnitude and type of physiological responses and the adaptations to resistance training can be shaped through the manipulation of these variables. One of the most important stimulus is the exercise intensity or load, which has been generally identified with relative load (González-Badillo & Sánchez-Medina, 2010; Jovanović & Flanagan, 2014). Relative load is commonly understood as percentage of one-repetition maximum (% of 1RM), which has typically two different methods for its measurements. When trainers identify the athlete's 1RM values for each exercise used in their training program through direct 1RM assessments, it is commonly referred to as the direct method (Jovanović & Flanagan, 2014). This method faces a number of issues such as the effect of athletes' experience, technique, fatigue and motivation on the outcome, the time consumption (McMaster, Gill, Cronin, & McGuigan, 2014) as well as the temporary deterioration of the function of the tested muscles (Niewiadomski, Gąsiorowska, Cybulski, Laskowska, & Langfort, 2008) and the «degree of concern over risk of musculoskeletal injury when the system is subjected to such high loads» (Mann, Stoner, & Mayhew, 2012, p. 2623). Contrarily, the indirect method using predictive models such as performing reps to fatigue or using the movement velocity is a much more simple, safe and accurate procedure to estimating the 1RM load (Carroll, Sato, Bazylar, Triplett, & Stone, 2017; González-Badillo & Sánchez-Medina, 2010; Jidovtseff, Harris, Crielaard, & Cronin, 2011; LeSuer, McCormick, Mayhew, Wasserstein, & Arnold, 1997; L. Sánchez-Medina, González-Badillo, Pérez, & Pallarés, 2014; Luis Sánchez-Medina, Pallarés, Pérez, Morán-Navarro, & González-Badillo, 2017;

Sayers et al., 2018). Table 1 gives an overview of the analyzed 1RM prediction formulas for this thesis. The first formula is based on Reps-to-Fatigue (Epley, 1985) and is followed by two Load-Velocity relationship formulas (Jovanović & Flanagan, 2014; Sayers et al., 2018) with their corresponding adaptations.

Table 1

An overview of the analyzed 1RM prediction formulas and the abbreviations used to simplify further reading

Author	Abbr.	Formula
Epley (1985)	Epley	%1RM = weight lifted / (1.0278 - (0.0278 * No. of reps)) %1RM = weight lifted * (36 / (37 - No. of reps))
Jovanović & Flanagan (2014)		%1RM = m(Velocity) + b ± Z(SEE) %1RM = slope ^{VMean} *MVT + intercept ^{VMean} ± Z(SEE)
VPeak method based on Jovanović & Flanagan (2014)	Jovanović	%1RM = slope^{VPeak} * MVT + intercept^{VPeak}
Sayers et al. (2018)		%1RM = $\frac{V_{mean}-3.2364}{-2.9503} * 100$
VMean5 method based on Sayers et al. (2018)	Sayers	%1RM = -100 * intercept^{VMean5} / slope^{VMean5}

Notes. Abbr. = abbreviations of terms, which are used for the graphs; weight = total weight used in [kg]; reps = total reps performed; Z = represents the desired level of confidence (LOC); slope = steepness of the linear regression; MVT = minimum velocity threshold; intercept = the place where the line crosses the y-axis; *Vpeak* = peak bar velocity; *Vmean* = average bar velocity; *VMean5* = the average velocity of the first 5 performed repetitions

To predict the 1RM with submaximal load Jovanović and Flanagan (2014) created a prescription of performing up to 3 reps in 5 consecutive sets (2-3 reps @ 30-40 % 1RM, 2 reps @ 40-50 % 1RM, 1-2 reps @ 60-70 % 1RM, 1 rep @ 70-80 % 1RM and 1 rep @ 80-85 % 1RM). Their formula used *V_{mean}* and was adapted to *V_{Peak}* in order to fit the used method in this thesis. In addition, Jovanović and Flanagan (2014) also used the «regression line and associated parameters such as slope and intercept point on the Y axis» (Jidovtseff et al., 2011, p. 267) and combined them with previously analyzed minimum velocity thresholds (MVT) for the barbell bench press (BBP) and the barbell back Squat (BBSq). «MVT is the mean concentric velocity produced on the last successful repetition of a set to failure performed with maximal lifting effort» (Jovanović & Flanagan, 2014, p. 61). It can be claimed that the MVT «remains stable regardless of strength level and is true irrespective of the number of reps performed» (Turner, 2017), as there is no significant difference between the average MVT performed during the last repetition of sets at 75 %, 70 %, 65 % and 60 % of 1RM (Izquierdo et al., 2006). Jidovtseff et al. (2011) also discussed that MVT have shown to be exercise specific. Table 2-4 shows an overview of different MVT according to different authors for each of the tested exercises: barbell bench press, barbell back squat and barbell deadlift.

Table 2

Summary of the minimal velocity threshold (MVT) for the BBP exercise (adapted from Baker, 2017) categorized into author, exact exercise performed, description of subjects (number, sports type and bodyweight), strength capacity (1RM) and concluded MVT

author	exercise description	subjects	strength capacity	velocity at 1RM (i.e., MVT [m/s])
BARBELL BENCH PRESS				
(González-Badillo & Sánchez-Medina, 2010)	(isoinertial) concentric bench press on a smith machine	120 strength-trained males; 78.3 kg bodyweight	1RM = 87.8 ± 15.9 kg	0.16 ± 0.04
(Helms et al., 2017)	bench press according to the rules of the International Powerlifting Federation (IPF)	15 experienced powerlifters 12 male @ 87.9 ± 16.3 kg 3 female @ 59.0 ± 5.8 kg	1RM = 114.94 ± 24.63 kg	0.10 ± 0.04
(Izquierdo et al., 2006)	concentric bench press (1cm above chest) on a smith machine	36 male Basque ball players; 80 kg bodyweight	1RM = 91 ± 17 kg	0.15 ± 0.03 0.17 ± 0.04 @75 % 0.18 ± 0.05 @70 % 0.18 ± 0.05 @65 % 0.17 ± 0.06 @60 %
(Jidovtseff et al., 2011)	concentric bench press (3cm above nipple line) on a smith machine	112 mixed subjects; 72 ± 14 kg bodyweight	1RM = 60 ± 19 kg	0.23 ± 0.09
(Ormsbee et al., 2017)	free weight touch & go bench press	13 college-aged novice benchers; 82.3 kg bodyweight	1RM = 89.5 kg	0.20 ± 0.05
(Ormsbee et al., 2017)	free weight touch & go bench press	14 college-aged experienced benchers; 90.2 kg bodyweight	1RM = 133.0 kg	0.14 ± 0.04
(Pallarés, Sánchez-Medina, Pérez, De La Cruz-Sánchez, & Mora-Rodriguez, 2014)	smith machine paused (2s) bench press	17 resistance-trained athletes 81.4 kg bodyweight	1RM = 89.1 kg	0.22
(Pallarés et al., 2014)	free weight touch and go bench press	17 resistance-trained athletes 81.4 kg bodyweight	1RM = 92.1 kg	0.19
(L. Sánchez-Medina et al., 2014)	(isoinertial) concentric bench press on a smith machine	75 male junior and senior national-level athletes (wrestling, canoeing, rowing or judo) 76.0 ± 8.8 kg bodyweight	1RM = 90.3 ± 16.3 kg	0.17
(Turner, 2017)	bench press	68 professional rugby players	1RM = 140 ± 16 kg	0.15 ± 0.03

Table 3

Summary of the minimal velocity threshold (MVT) for the BBSq exercise (adapted from Baker, 2017) categorized into author, exact exercise performed, description of subjects (number, sports type and bodyweight), strength capacity (1RM) and concluded MVT

author	exercise description	subjects	strength capacity	velocity at 1RM (i.e., MVT [m/s])
BARBELL BACK SQUAT				
(Carroll et al., 2017)	high bar back squat on force platform	14 recreationally trained males; 88.2 \pm 15.8 kg bodyweight		0.28 \pm 0.07
(Conceição, Fernandes, Lewis, González-Badillo, & Jiménez-Reyes, 2015)	smith machine paused (3-4s) full squat	15 male track and field athletes; 70.1 \pm 14.5 kg bodyweight	1RM = 124.2 \pm 26.6 kg	0.30 \pm 0.04
(Helms et al., 2017)	barbell back squat according to the rules of the International Powerlifting Federation (IPF)	15 experienced powerlifters 12 male @ 87.9 \pm 16.3 kg 3 female @ 59.0 \pm 5.8 kg	1RM = 172.41 \pm 32.84 kg	0.23 \pm 0.05
(Izquierdo et al., 2006)	parallel back squat on smith machine	36 male Basque ball players; 80 kg bodyweight	1RM = 200 \pm 20 kg	0.27 \pm 0.02 0.31 \pm 0.06 @75 % 0.32 \pm 0.07 @70 % 0.31 \pm 0.06 @65 % 0.33 \pm 0.07 @60 %
(Pallarés et al., 2014)	smith machine paused (2s) squat (PSq)	17 resistance-trained athletes	1RM = 90.3 kg	PSq = 0.37
	smith machine squat (Sq)	81.4 kg bodyweight		Sq = 0.39
(Turner, 2017)	box squat	12 professional rugby players		0.25 \pm 0.03
(Zourdos et al., 2016)	back squat	14 novice squatters training age: 0.4 \pm 0.6 years 80.3 kg bodyweight	1RM = 91.2 kg	0.34
(Zourdos et al., 2016)	back squat	15 experienced squatters training age: 5.2 \pm 3.5 years 91.6 kg bodyweight	1RM = 171.9 kg	0.24 \pm 0.04

Table 4

Summary of the minimal velocity threshold (MVT) for the BDL exercise categorized into author, exact exercise performed, description of subjects (number, sports type and bodyweight), strength capacity (1RM) and concluded MVT

author	exercise description	subjects	strength capacity	velocity at 1RM (i.e., MVT [m/s])
BARBELL DEADLIFT				
(Helms et al., 2017)	deadlifts according to the rules of the International Powerlifting Federation (IPF)	15 experienced powerlifters 12 male @ 87.9 \pm 16.3 kg 3 female @ 59.0 \pm 5.8 kg	1RM = 213.46 \pm 41.05 kg	0.14 \pm 0.05

1.2 Velocity based training

In order to understand the importance of MVT, VBT has to be discussed more thoroughly. VBT belongs together with Flexible Periodization, Auto-regulatory Progressive Resistance Exercise, Rating of Perceived Exertion (RPE) and Heart Rate Variability (Fisher, 2016) to the common methods of auto-regulation and will be used for further analyses in this thesis. It is based upon the common understanding that «as the load of a given lift increases (and maximal intent to lift it as fast as possible is applied), the speed at which it moves decreases in a linear fashion» (Turner, 2017). A number of researchers have stated that the relationship between load and mean concentric velocity is extremely stable and very strong in the simple strength exercises bench press and back squat (González-Badillo & Sánchez-Medina, 2010; Jidovtseff et al., 2011). On account of commercially available linear position transducers (LPT) (such as the GymAware, T-FORCE or the Tendo Power), the «velocity of lifting can now be easily and reliably measured in many basic strength training exercises» (Jovanović & Flanagan, 2014, p. 59). The three LPT mentioned above were thoroughly studied on their reliability and validity of the parameters V_{max} , V_{mean} and $t V_{max}$ (Lorenzetti, Lamparter, & Lüthy, 2017). Their findings for the evaluation of squat performance at different squatting speeds suggest that all three LPT devices are reliable. «In particular, the parameters V_{mean} and $t V_{max}$ can be used to monitor and guide workouts» (Lorenzetti et al., 2017, p. 4). The Root Mean Square Error (RMSE) of V_{max} was in traditional squats (RMSE between 0.151 and 0.194) as well as ballistic squats (RMSE between 0.263 and 0.315) larger than the other parameters and indicates its value being a less robust measure.

1.2.1 Benefits and disadvantages of VBT. It is important to know that the application of the velocity-based approach involves different levels of implementation in contrast to an all-or-nothing implementation (Jovanović & Flanagan, 2014) and can, therefore, be used together with a percent-based periodization program. For example, the 1RM can be estimated from sub-maximal loads using the velocity-based approach and then be implemented into a resistance training program that uses percent-based variables. 1RM predictions from sub-maximal loads show big advantages to 1RM predictions from direct methods as already mentioned in chapter 1.1 (Carroll et al., 2017; Jidovtseff et al., 2011; Sanchez-Medina, Perez, & Gonzalez-Badillo, 2010; Luis Sánchez-Medina et al., 2017; Sayers et al., 2018). Furthermore, those 1RM predictions can be done on a more regular basis without interfering the periodization or compromising injuries or even be done daily with the help of LPT. LPT that have the possibility of displaying live feedback on current movements have shown to be beneficial towards athletes' performances, if they are already intrinsically motivated to reach a target

velocity measurement (Jovanović & Flanagan, 2014; Kilduski & Rice, 2003; Randell et al., 2011). This live feedback, if properly implemented into one's resistance training, can also be used as a method of auto-regulation that optimizes training and avoids under- and overtraining (Fleck & Kraemer, 2014). Auto-regulation of training according to the athletes readiness level for each training session can be performed through adjustments of load and the number of sets and repetitions (Jidovtseff et al., 2011) and holds a beneficial factor against traditional periodization of resistance training programs that solely rely on a periodical measurement of the athlete's 1RM.

Another benefit of VBT is that maximal concentric velocity is encouraged (Fisher, 2016; Jovanović & Flanagan, 2014; Turner, 2017). This is most profitable for power athletes, contact sports, throwing events (e.g. shot put and hammer throw) and weightlifters (McMaster et al., 2014; Singh, 2016) who have a limited window to apply the maximal amount of force. As power equals the product of multiplying force by velocity, «increasing the velocity will increase the power output of the exercise without needing to increase or decrease the load if one is capable of doing so» (Fisher, 2016, p. 3). Completing an explosive movement with a maximum effort forces the neurons to select the fast twitch motor units first. This phenomenon is called selective recruitment (Datta & Stephens, 1981; Lin & Chen, 2012) and suggests the understanding that motor units with high activation thresholds (type IIa and type IIx fast twitch motor units) are activated before the motor units with lower activation thresholds (type I slow twitch motor units). The selective recruitment phenomenon stands opposite the Henneman's size principle (Henneman, 1957). Henneman demonstrated that as the level of force increases motor units were recruited in order of increasing size. Even though Henneman's findings were based on working with anesthetized cats, his fundamentally important finding was later strongly confirmed by Milner-Brown, Stein, and Yemm (1973). Their results «provide the first direct evidence that motor units are recruited during increasing voluntary contraction in an orderly fashion according to the size of contraction they produce» (p. 367). As already mentioned, an athlete using VBT would therefore benefit from directly targeting the type IIa and type IIx fast twitch motor units. At the same time those two principles show a disadvantage of the VBT, especially regarding the regulation of muscular hypertrophy, as training to complete muscle failure is not encouraged through the constant focus on maximal concentric velocity.

Through the constant focus on maximal concentric velocity an individual strength quality profile for each athlete can be concluded, analyzed and further used for comparisons of different athletes (Turner, 2017). This holds a big benefit compared to solely relying on 1RM tests. For example, two athletes with the same 1RM for the back squat can show performances with

different velocities in submaximal loads, which may show significant importance for their programming and transferring their performances onto the field. It is therefore of utmost importance to thoroughly comprehend the athletes' purpose on the field and then properly adjust their work load, performance output and ultimately their programming.

As can be seen by now, another factor which has to be taken into account is the time used for proper adjustments of the training and the programming. The LPT have to be studied carefully and understood in depth before being used with a group of athletes. Furthermore, as the costs of LPT are already high, the chances of having more than one LPT to one's disposal is rare. Therefore, a focus has to be set on a specific exercise, as the time for the preparation, installation and dismounting of the equipment also has to be taken into consideration. All this depends on the group size and the exercises being tested. The high costs of LPT cause a major disadvantages for VBT, which is the reason why Lorenzetti et al. (2017) suggested that future research should focus on «more valid and reliable devices for a cheaper prize» (p. 4). Hence, the next chapter focuses on Huber's findings (Huber, 2017) and his strength training app.

1.3 Huber's strength training app

Huber's thesis (Huber, 2017) was based on account of the following four statements, that chronic diseases will cause the biggest health care expenses in the future (Fleck & Kraemer, 2014; Seeger, Buchmann, & Van Laerhoven, 2011; World Health Organization, 2018), that even regular and moderate physical activity would reduce the rate of different chronic diseases (Carroll et al., 2017), that physical activity can be supported and promoted by workout assistants (Seeger et al., 2011), that various aerobic workout assistants have already been successfully introduced on the market compared to the lack of strength training workout assistance (Pernek, Hummel, & Kokol, 2013). Hence, his thesis focused on four main objectives.

First of all, he developed a workout analysis application using a recognition algorithm that can be used for the Apple Watch and iPhone and, therefore, drops the costs for an additional LP. He used a recognition algorithm that was developed and provided by FocusMotion. This algorithm was fully integrated into the watchOS and showed high functionality despite being in an early development stage. The weight could be entered through the Digital Crown on the smartwatch right after the set and further corrected on the iPhone App once imported. The same goes for the recognized exercise and repetition counting. If the exercise or the performed repetitions were not accurate, they could as well be changed with the help of the Digital Crown.

In his second objective, he determined the accuracy of the exercise recognition and repetition counting. The data was collected with a reduced sample size of one male sports student and

showed an overall exercise recognition error with a low mean of 3.49 %error, a median of 0.00 %error and a high standard deviation (SD) of 18.46 %error. The tested exercises were biceps curl with twist, barbell biceps curl, dumbbell lateral raise, barbell bench press and barbell back squat, each performed with either 5 or 10 repetitions. His findings showed a high accuracy of exercise recognition comparable to other authors that had 2.0 %error with 9 exercises (Zhang et al., 2016), 2.3 %error with 3 exercises (SooHyun & SooWon, 2016), 7.0 %error with 12 exercises (Guo, Liu, & Chen, 2016) and 44.2 %error with 30 exercises (Koskimäki & Siirtola, 2016). The overall repetition counting %error ($N = 83$) showed a low mean of 0.92 %error and a low median of 0.00 %error, which can be partly explained due to neutralization of positive and negative values. The RMSE was not calculated, but the results showed a high SD of 21.74 %error. His findings have shown again comparable results to a 1.0 %error with 5 exercises (Pernek et al., 2013) and 2.0 %error with 6 exercises (Zhang et al., 2016). Huber concluded that, even though, his implemented recognition algorithm has shown a high accuracy in exercise detection and repetition counting and can be used as an accurate method to log workouts, further investigation with a larger sample size has to be conducted.

For the third objective, Huber then implemented an estimation for the 1RM, as most research that used smartwatches for exercise recognition (Guo et al., 2016; Koskimäki & Siirtola, 2016; SooHyun & SooWon, 2016; Zhang et al., 2016) and repetition counting (Pernek et al., 2013; Zhang et al., 2016) did not include that. The estimate 1RM was calculated with a formula that uses the velocity parameter V_{mean} (Sayers et al., 2018). Two different testings of 5 sets each of 60 % and 80 % of the 1RM, that was determined with the direct method, were then conducted and compared solely performing the barbell bench press. The results for the 60 % 1RM estimation have shown a mean of 0.28 %error with a SD of 1.70 %error and for the 80 % 1RM estimation a mean of 7.80 %error and a SD of 28.19 %error. The explanation for those results were based on possible imprecise execution and the fact of it being a low sample size. Huber also states that one of the biggest limitations of using the velocity parameter with the smartwatch was that it «is calculated by a non-alterable distance leading to wrong data if the user has a different height or does not use the same range of motion» (p. 63). Nevertheless, Huber concluded a successful implementation of the 1RM estimation for the barbell bench press exercise and suggested further investigation with other exercises and a larger sample size.

Huber's fourth and last objective of developing and implementing a muscle fatigue parameter was not thoroughly concluded and will not be taken into consideration in this thesis.

Out of all these findings the objective of this thesis was formulated as followed.

1.4 The objective of the thesis

The primary aim of this thesis, was the comparison of different 1RM prediction methods that use either load-velocity relationship measurements or reps-to-fatigue relationship measurements as shown in detail in table 1 and which can be implemented into the strength training app. Hereby, the research question was:

- a) Which load-velocity or reps-to-fatigue formula and which parameters are the most suitable for a future strength training app integration?

As to this point, the app has only been tested by one test subject. Hence, the secondary aim of this thesis will be on analyzing the validity, reliability and accuracy of the app's functions and the quality of results with a broader subject group and additional exercises. The data will be compared with the results of the LPT GymAware PowerTool, that has already been tested on its validity in many research studies (Dorrell, Moore, Smith, & Gee, 2018; Orange et al., 2018; Turner, 2017). Other wearables and smartphone-based technologies (Balsalobre-Fernández, Kuzdub, Poveda-Ortiz, & Campo-Vecino, 2016; Balsalobre-Fernández et al., 2017) have also been testing their data with the same means. The results will be presented in %error and the tested parameters will be *exercise recognition*, *repetition counting* and *1RM prediction* with the exercises barbell bench press, barbell back squat and barbell deadlift. Therefore, the asked research questions were:

- b) Does the app give accurate readings on the parameter *exercise recognition* with all three exercises compared?
- c) Does the app give accurate readings on the parameter *repetition counting* compared to real life performances?
- d) How precise are the *1RM predictions* of the app compared to the load-velocity or reps-to-fatigue approach by Jovanović and Flanagan (2014), Sayers et al. (2018) and Epley (1985)?

2 Methods

2.1 Experimental Approach to the Problem

As Jidovtseff et al. (2011) suggested, in order to predict 1RM from AV-load relationship, AV was measured at 4 increasing loads, starting with a light load. The MVT used for the adapted formula of Jovanović and Flanagan (2014) are 0.15 for BBP, 0.25 for BBSq and 0.3 for BDL as the subject group consists of recreationally resistance-trained males and females and not specifically Powerlifters, which tend to show lower MVT values.

2.2 Subjects

The analyzed subject group consisted of 30 (16 female, 14 male) physically healthy athletes ($M_{\text{age}} = 28.4$, $SD = 6$, range 19 – 41, Table 6) with a heterogeneous history of strength training ($M_{\text{training}} = 4.8$ years, $SD = 3.9$, range 0.5 – 17, Table 6) and all participating in their own weight training program 1 - 4 days a week. The detailed physical characteristics are presented in Table 7 with mean and SD. The sample size of 30 subjects comes from a recommendation for correlational studies that relate variables (Creswell, 2012). The subjects were found through posts on the facility's platform and by E-mail to the Bachelor students of the University of Bern, the University of Fribourg and the Swiss Federal Institute of Sports Magglingen and they volunteered to take part in this study. All subjects were informed of the nature of the study and signed an informed consent. The Cantonal Research Ethics Commission of Bern, Switzerland approved this study (project-ID: 2016.01970).

2.3 Equipment and Resources

The material used consisted of an Apple Watch Sports 1st Generation, iPhone 6s, MacBook Pro, iPad Air, GymAware PowerTool, a standard olympic barbell (20kg = 44lbs), weight plates (5 - 20kg = 11 - 44lbs), measuring tape (for the body height), body scale (for the body weight). The Apple Watch Sports 1st Generation was connected to an iPhone 6s with the iOS 11.4.1. The GymAware PowerTool was attached with the Velcro Strap around the bar according to the instructions of the manufactures, so a perpendicular angle was achieved during all lifts and was then paired through Bluetooth to an iPad Air. Both the iPhone and the iPad had the corresponding App (GymAware, v2.5.1, ©2014-18 Kinetic Performance Technology Pty Ltd and Strength Control, v1.8, Betatester) for data acquisition installed.

The data was collected at either the UNIK Training¹ gym facility in Bern, the ZSSw gym² at the Center of Sports and Sport Sciences of the university of Bern or at the athletic Training³ gym facility in Thun.



Fig. 1. Measurement devices as used for the three exercises: (1) Apple Watch Sports, (2) GymAware PowerTool

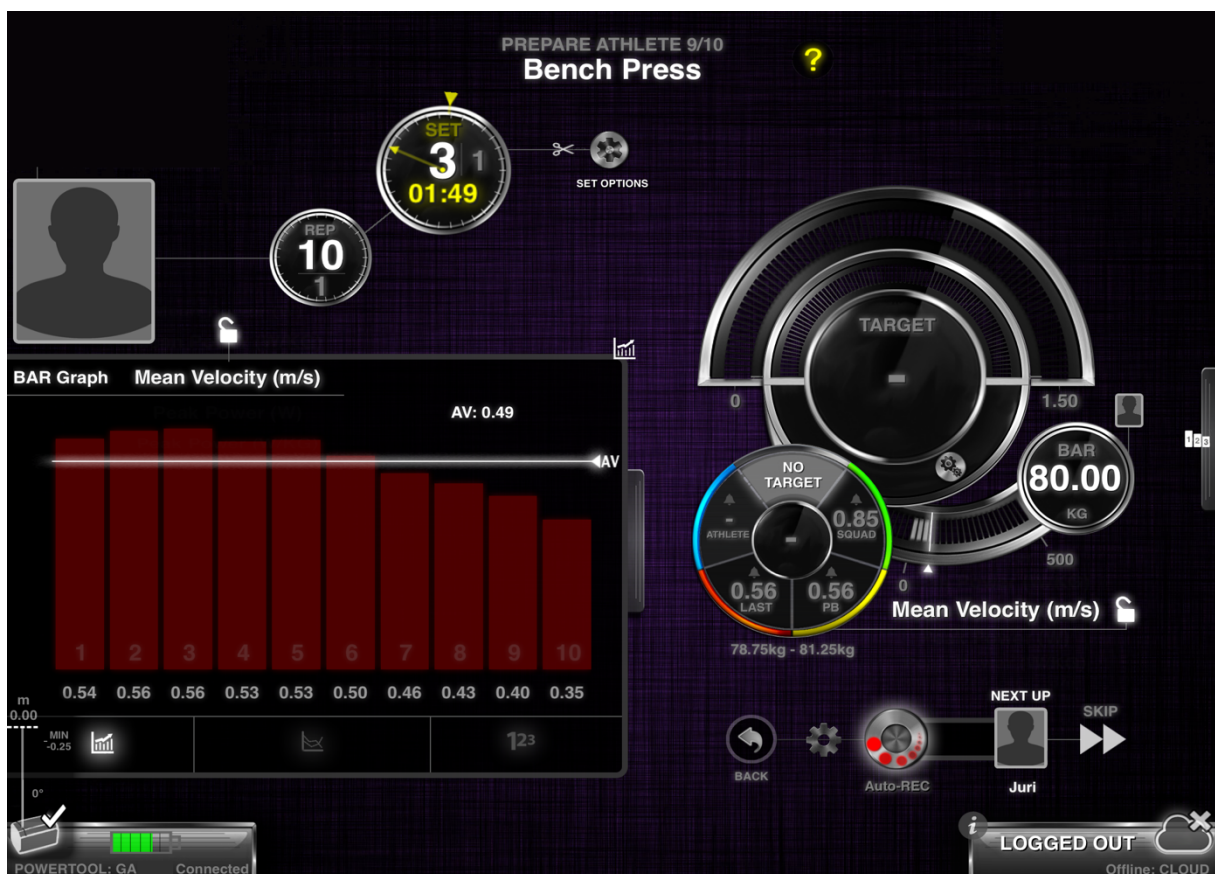


Fig. 2. Exemplary interface of the GymAware App for the iPad with an athlete performing a set of 10 repetitions on the barbell benchpress. The most typically seen velocity curve can be observed with the peak velocity occurring during the first five reps.

¹ UNIK Training, Bolligenstrasse 82, CH-3006 Bern

² ZSSw gym, Center of Sports and Sport Science, Bremgartenstrasse 145, CH-3012 Bern

³ athletic Training – Functional Training Thun, Gewerbstrasse 15, CH-3600 Thun

2.4 Procedures

All 30 subjects performed the three exercises in the following order: barbell deadlift, barbell bench press, barbell back squat. They performed 4 consecutive sets with increasing loads (adopted from Jidovtseff et al., 2011) that corresponded to 60 – 80 % of their estimated 1RM. The goal for each set was to perform no more than 10 repetitions (Reynolds, Gordon, & Robergs, 2006) . If the subject's estimated 1RM was way off, an additional fifth set was performed until fatigue during the 10 reps was occurring. Subjects were allowed adequate rest (3-5 minutes) between each set (Nimphius, McGuigan, & Newton, 2012; Shimano et al., 2006). The exercise instructions (Huber, 2017) were given to the subjects as shown in Table 5.

Table 5

The measurement process with the corresponding tasks and exercise instruction

		Task/Exercise Instruction
Pre-Measurement	Instruction 1	The measurement process is described and explained to the subject and the consent form is signed. The subject gives his estimated 1RM for each exercise
	Preparation	The subject changes clothes and gets ready for the individual warm up of around 10 minutes on the rower or bike. Meanwhile, the warm up set weight for the deadlift is prepared and the GymAware is attached to the Barbell.
	Instruction 2	The Apple watch is mounted on the subject's left wrist.
Measurement	Preparation BDL	The subject performs his/her warm up set and the GymAware and the Apple watch are being tested if they are sending data.
	BDL	“Stand in front of the loaded barbell about hip width apart. Keep your back straight and bend your knees to reach forward to grab the bar using a shoulder-width grip. Hold the bar and start the lift by pushing with your legs while keeping your torso as upright as possible. Keep the shoulder blades back as you do this. On top, hold the weight for a second with locked hips and knees. Return to the starting position by lowering the weights to the floor.” 4 Sets; 10 reps max or till failure; 3-5 min break in between sets
	Preparation BBP	The subject performs his/her warm up set and the GymAware and the Apple watch are being tested if they are sending data.
	BBP	“Lie back on a flat bench with your eyes under the bar. Grab the bar at about shoulder width. Unrack the bar by straightening your arms and position it directly above your chest. Slowly lower the bar to your mid-chest, touching it gently. Pause and then extend your arms, bring-

		ing the bar back to the starting position.” 4 Sets; 10 reps max or till failure; 3-5 min break in between sets
	Preparation BBSq	The subject performs his/her warm up set and the GymAware and the Apple watch are being tested if they are sending data.
	BBSq	“Use a squat rack and a straight bar to perform this exercise. Position the bar on your back, resting on your trapezius muscles. Hold the bar on both sides as you lower yourself into a squat position. Keep your back straight and let your knees go out in direction of your toes. As you come up keep your butt from going outward but instead keep your back straight. You don't want to bend forward as you extend your legs to return to starting position.” 4 Sets; 10 reps max or till failure; 3-5 min break in between sets
Post-Measurement	Dismissal	The subject is given the results from the Epley (1985), Brzycki (1993) and the Jovanović and Flanagan (2014) method and is informed about the further research process. In addition, the subject’s personal data (age, weight and height) is collected.
	Hygiene	The watch is disinfected and put back on the loading station to make sure the watch is ready for the next subject.
	Data Transfer	The data from the Apple watch is sent to the iPhone and then transferred to the Excel.

2.5 Data Analysis

Data was sampled through the iPad Air that is connected to the GymAware PowerTool and through the iPhone 6 that is connected to the Apple Watch Sport. Microsoft® Excel for Mac, version 16.20, enabled data analysis, storage of information and instantaneous presentation of results. The 1RM calculation was done through Epley’s formula (1985) using submaximal load.

2.6 Statistical Analyses

To express the accuracy of the exercise recognition, repetition counting and 1RM prediction the standard error estimate (SEE) was calculated as follows:

$$SEE = \sqrt{\frac{\sum(Y-Y_1)^2}{N}}$$

The numerator is the sum of squared differences between the actual scores (Y) and the predicted scores (Y₁). The denominator is the sample size (N). For each exercise the linear re-

gression line of the relationship between the predicted 1RM methods is plotted through the known load₁ (X) and known load₂ (Y) values. From these linear regressions the intercept (b), slope (a) and the coefficient of determination (R²) are calculated. In addition, a two-sample paired t-test was used to show the significance level with the chosen statistical significance threshold of 0.05. Furthermore, the magnitudes of the relationships between the predicted 1-RMs were interpreted using Pearson correlation coefficients, described as low (0.1-0.3), moderate (0.3-0.5), high (0.5-0.7) and very high (0.7-0.9) (Cohen, 1988; Hopkins, 2002; McGraw & Wong, 1992) and the Root Mean Square Error (RMSE) was used to measure how much error there is between each data set of 1RM predictions.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (f_i - o_i)^2}{n}}$$

where f is the predicted score (from the app) and the o is the observed score (true value). The line above the squared differences indicates the mean.

3 Results

3.1 Subjects

The recruitment lasted from September till November 2018 and the data was collected between October and November 2018 at one of the three previously mentioned locations (see chapter 2.4 Resources).

Table 6

Physical characteristics (mean \pm SD) for the overall subject group and for the two sex (M = male, F = female) and their corresponding predicted 1RM using the method of Epley (1985)

<i>Variable</i>	<i>Total (N = 30)</i>	<i>Men (N = 14)</i>	<i>Women (N = 16)</i>
Age (years)	28.4 \pm 6.0	28.1 \pm 6.5	28.6 \pm 5.8
Height (cm)	1.72 \pm 0.09	1.79 \pm 0.06	1.67 \pm 0.07
Weight (kg)	72.3 \pm 15.7	84.6 \pm 13.2	61.9 \pm 8,1
BMI	24.1 \pm 3.4	26.5 \pm 3.3	22.0 \pm 1.8
Years of training experience	4.8 \pm 3.9	6.8 \pm 4.8	3.1 \pm 1.7
1RM^{BBP} (kg)	70.6 \pm 34.5	96.5 \pm 36.9	43.9 \pm 7.6
1RM^{BBSq} (kg)	116.0 \pm 42.2	143.2 \pm 50.6	84.8 \pm 19.9
1RM^{BDL} (kg)	126.5 \pm 47.7	154.3 \pm 61.1	94.3 \pm 20.4

Notes. SD = standard deviation; BMI = body mass index; 1RM^{BBP} = predicted 1 repetition maximum for the barbell bench press; 1RM^{BBSq} = predicted 1 repetition maximum for the barbell back squat; 1RM^{BDL} = predicted 1 repetition maximum for the barbell deadlift

3.2 1RM predictions

The individual results and their predictions are shown in the appendix. The correlations of the three formulas are listed in the following chapter separated by exercise. All graphs have been standardized to the same maximal weight on the axes. To simplify the reading Jovanović and Flanagan (2014) was abbreviated as Jovanović and Sayers et al. (2018) to Sayers.

3.2.1 1RM predictions for the barbell bench press.

Table 7

Correlation data between 1RM predictions of the three methods (Epley, 1985; Jovanović & Flanagan, 2014; Sayers et al., 2018) for the barbell bench press

	b	a	R²	RMSE	p	r
Jovanović - Epley	3.4501	0.9638	0.9828	3.49	0.29	0.99
Sayers - Epley	1.8475	1.0501	0.9731	6.95	<0.01	0.99
Sayers - Jovanović	-1.2724	1.0792	0.9758	5.69	<0.01	0.99

Notes. b = intercept, a = slope, R² = coefficient of determination, RMSE = root mean square error, p = probability of paired t-test for difference; r = Pearson correlation coefficient

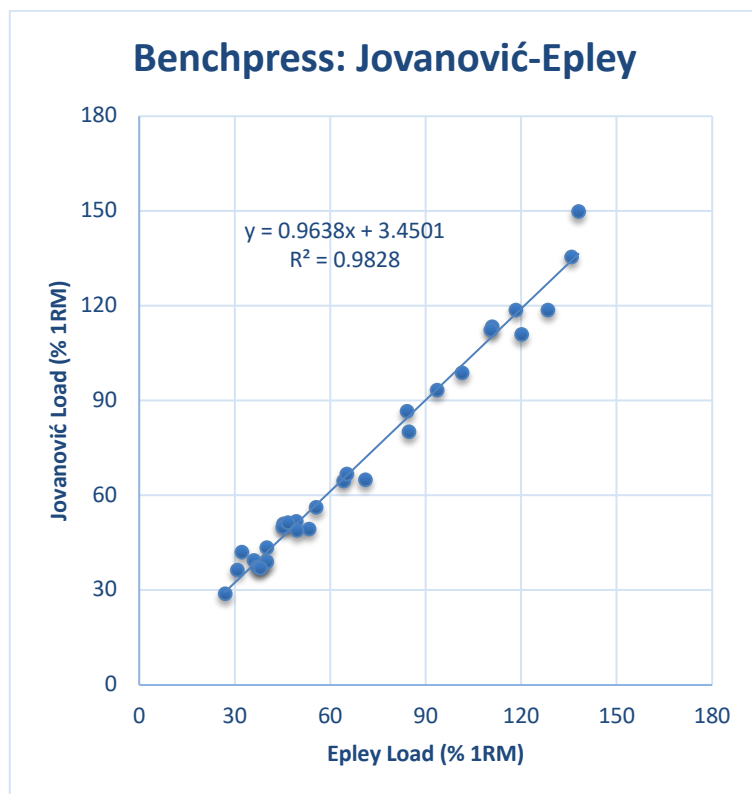


Fig. 3. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adaptation of the method suggested by (Jovanović & Flanagan, 2014) for the barbell bench press exercise.

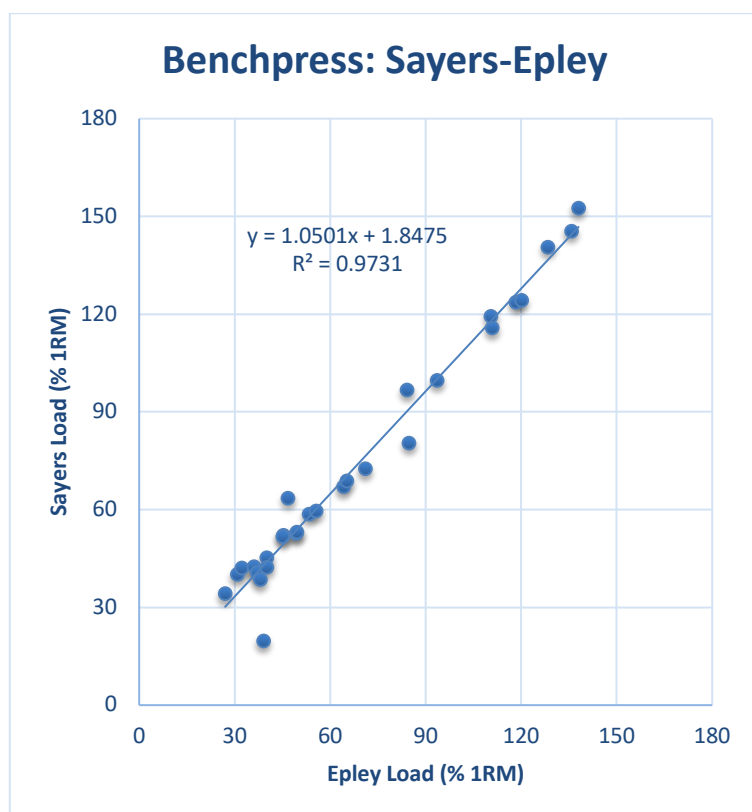


Fig. 4. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adapted (Sayers et al., 2018) method for the barbell bench press exercise.

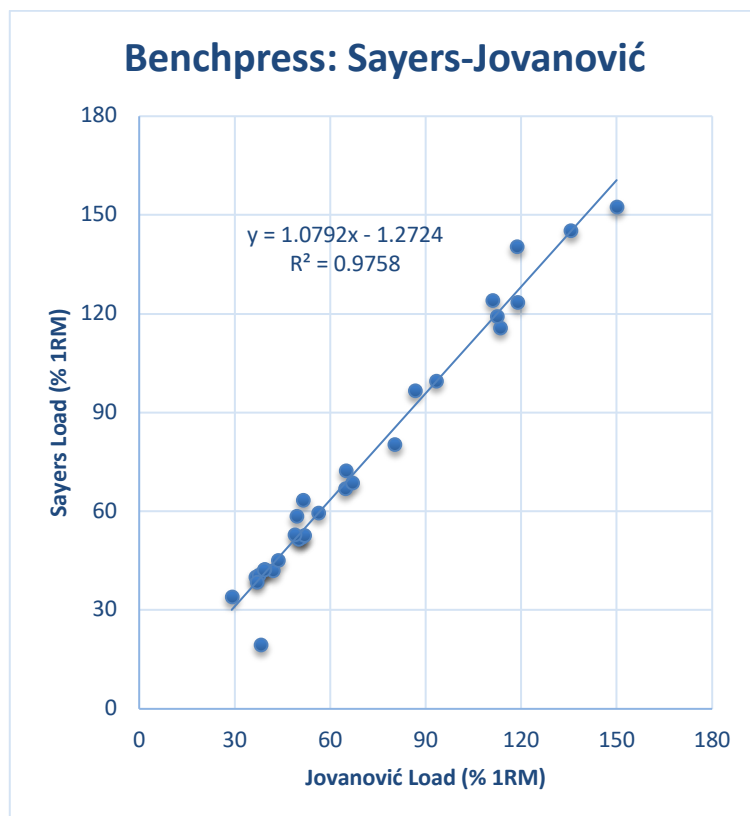


Fig. 5. Scatter plot with correlation between 1RM predictions attained from the adaptation of (Jovanović & Flanagan, 2014) method and the adapted (Sayers et al., 2018) method for the barbell bench press exercise.

3.2.2 1RM predictions for the barbell back squat.

Table 8

Correlation data between 1RM predictions of the three methods (Epley, 1985; Jovanović & Flanagan, 2014; Sayers et al., 2018) for the barbell back squat

	b	a	R ²	RMSE	p	r
Jovanović - Epley	2.3348	1.0808	0.8556	12.15	<0.01	0.93
Sayers - Epley	18.3320	1.2574	0.6868	45.48	<0.01	0.91
Sayers - Jovanović	13.7780	1.1793	0.8248	34.58	<0.01	0.83

Notes. b = intercept, a = slope, R² = coefficient of determination, RMSE = root mean square error, p = probability of paired t-test for difference; r = Pearson correlation coefficient

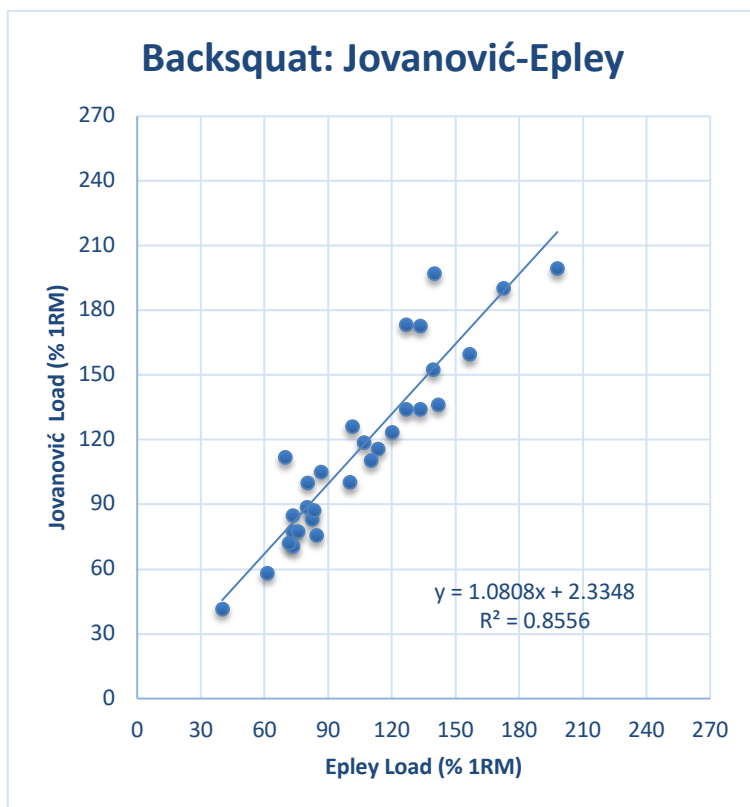


Fig. 6. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adaptation of the method suggested by (Jovanović & Flanagan, 2014) for the barbell back squat exercise.

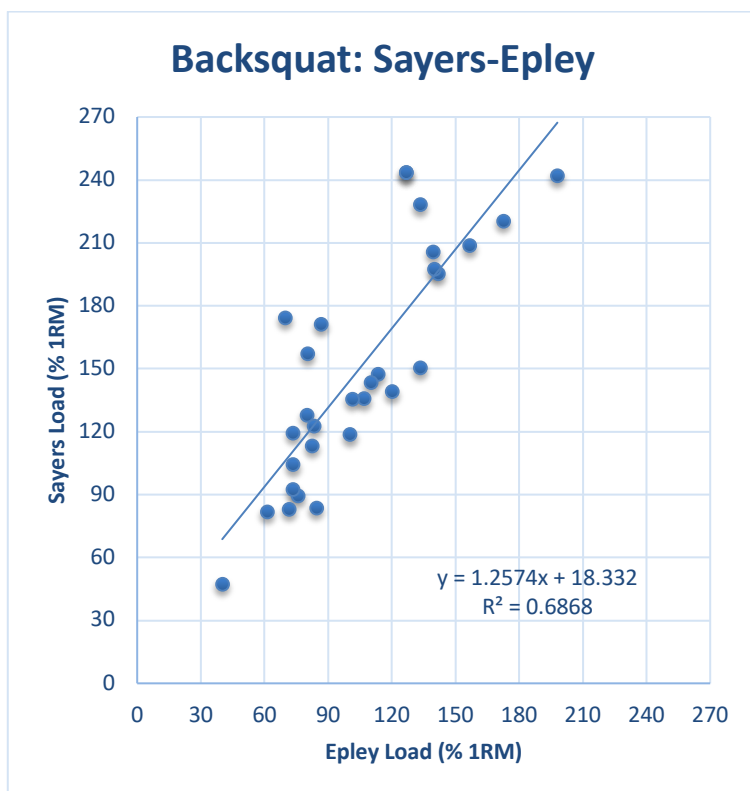


Fig. 7. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adapted (Sayers et al., 2018) method for the barbell back squat exercise.

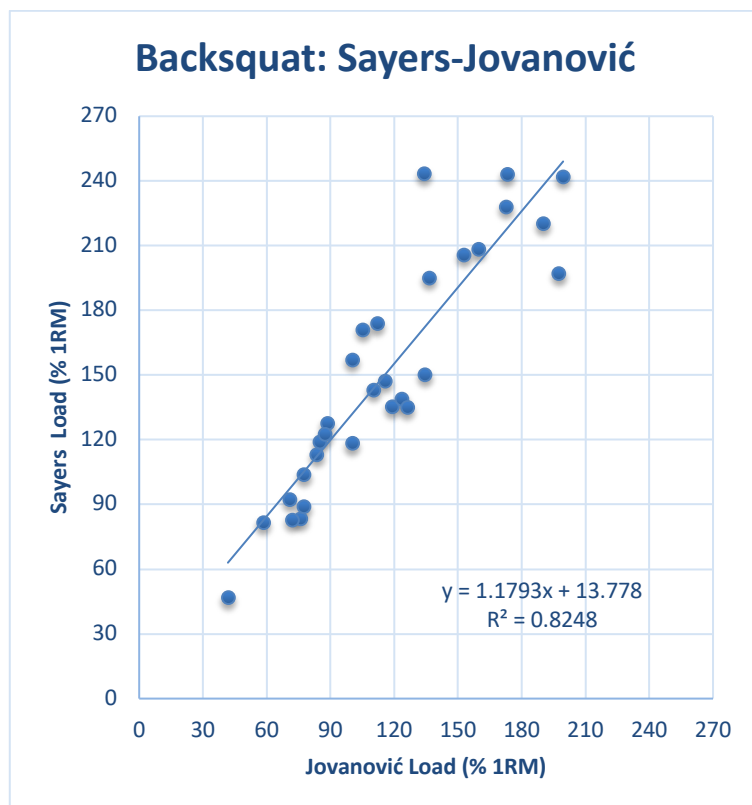


Fig. 8. Scatter plot with correlation between 1RM predictions attained from the adaptation of (Jovanović & Flanagan, 2014) method and the adapted (Sayers et al., 2018) method for the barbell back squat exercise.

3.2.3 1RM predictions for the barbell deadlift.

Table 9

Correlation data between 1RM predictions of the three methods (Epley, 1985; Jovanović & Flanagan, 2014; Sayers et al., 2018) for the barbell deadlift

	b	a	R ²	RMSE	p	r
Jovanović - Epley	10.0060	0.9908	0.8309	14.90	0.02	0.91
Sayers - Epley	33.7060	1.2448	0.5451	63.09	<0.01	0.89
Sayers - Jovanović	5.1514	1.3827	0.7946	53.57	<0.01	0.74

Notes. b = intercept, a = slope, R² = coefficient of determination, RMSE = root mean square error, p = probability of paired t-test for difference; r = Pearson correlation coefficient

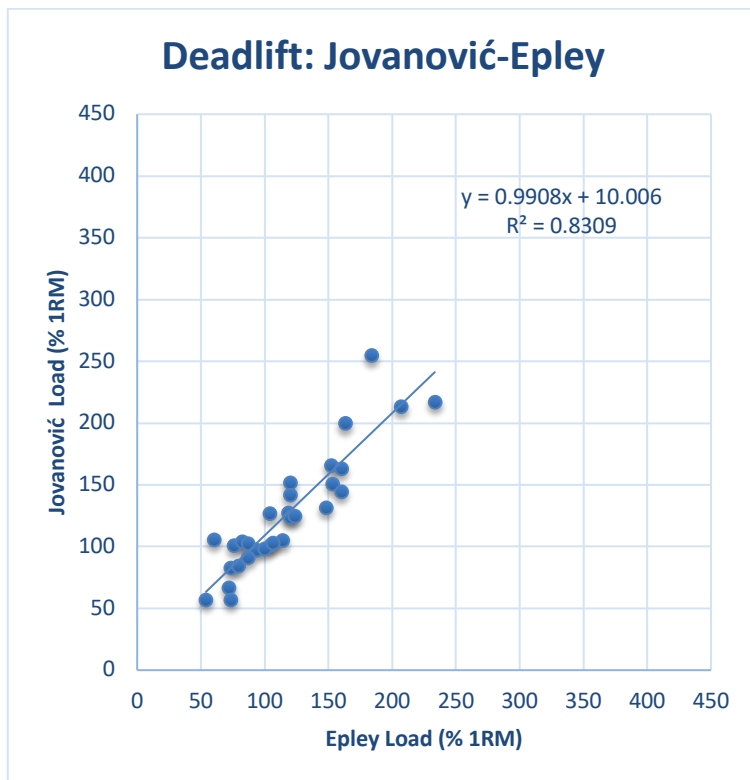


Fig. 9. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adaptation of the method suggested by (Jovanović & Flanagan, 2014) for the barbell deadlift exercise.

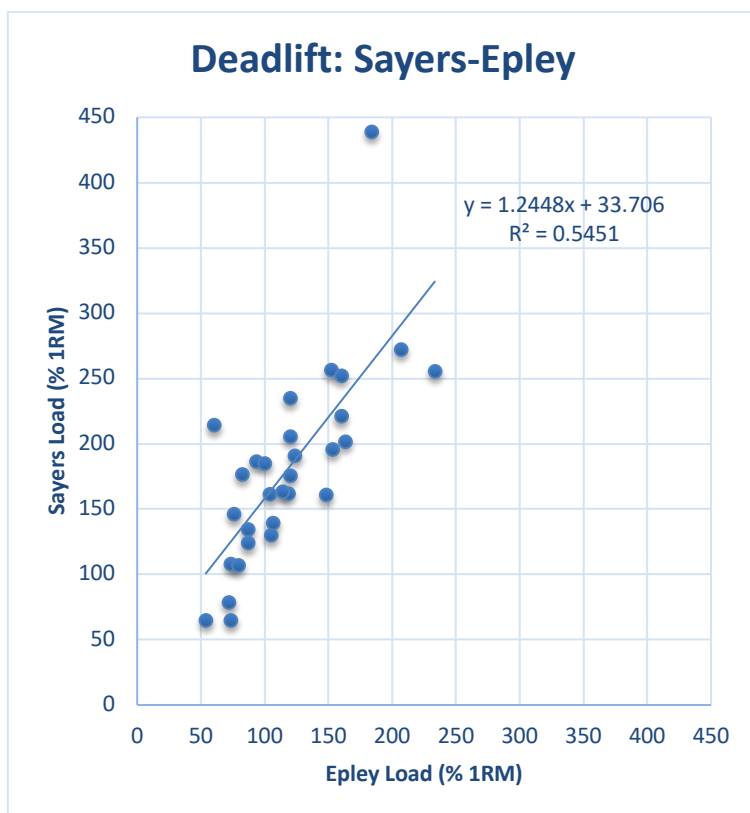


Fig. 10. Scatter plot with correlation between 1RM predictions attained from the (Epley, 1985) method and the adapted (Sayers et al., 2018) method for the barbell deadlift exercise.

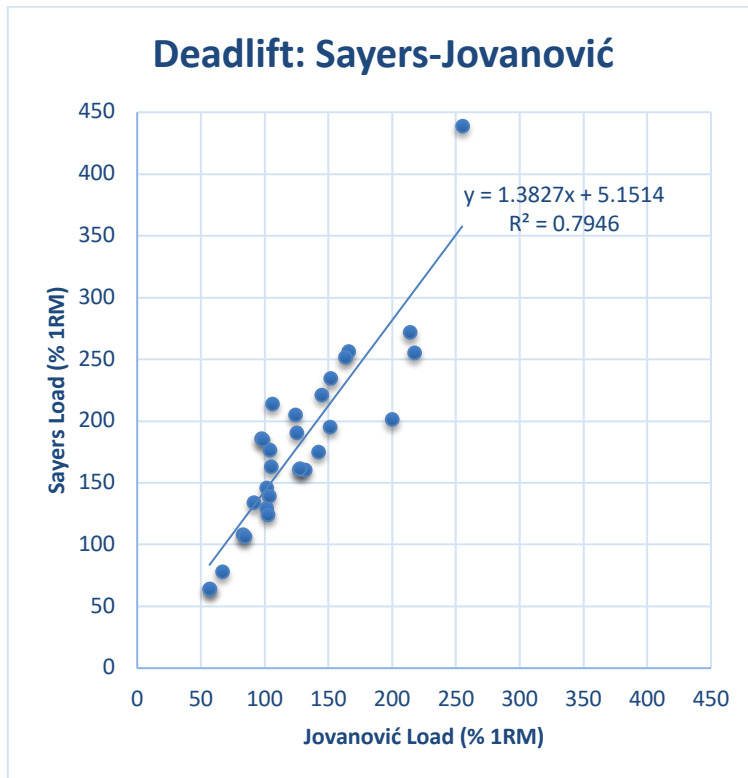


Fig. 11. Scatter plot with correlation between 1RM predictions attained from the adaptation of (Jovanović & Flanagan, 2014) method and the adapted (Sayers et al., 2018) method for the barbell deadlift exercise.

3.2.4 MVT. The minimum velocity threshold (MVT) for the barbell bench press was the lowest with 0.16 ± 0.05 , followed by the barbell back squat with 0.35 ± 0.09 and the barbell deadlift with 0.45 ± 0.13 . The barbell deadlift has the biggest range of results.

Table 10

Average, SD and range of minimum velocity threshold for every exercise

<i>N = 30</i>	<i>BBP</i>	<i>BBSq</i>	<i>BDL</i>
<i>M</i>	0.16	0.35	0.45
<i>SD</i>	0.05	0.09	0.13
<i>Range</i>	0.08 – 0.28	0.22 – 0.56	0.27 – 0.81

Notes. N = number of subjects; M = average; SD = standard deviation; Range = range of results (spreading of data); BBP = barbell bench press; BBSq = barbell back squat; BDL = barbell deadlift

3.3 Detection accuracy of the app

3.3.1 Exercise recognition. Overall 88.4 % of all performed sets (N = 363) were recognized with the correct exercise. Most accurate was the BBP exercise with 96.5 % followed by BDL with 92.2 % and the BBSq with 76.5 %. Table 11 gives a more detail overview concerning the different exercises. The confusion matrix in Table 12 reveals tendencies in mistaking different exercises.

Table 11

Exercise recognition accuracy of the three exercises

	<i>N</i>	<i>TRUE</i>	<i>FALSE</i>	<i>% TRUE</i>	<i>% FALSE</i>
BBP	119	115	4	96.5 %	3.5 %
BBSq	121	98	23	76.5 %	23.5 %
BDL	124	115	9	92.2 %	7.8 %
total	363	327	36	88.4 %	11.6 %

Notes. N = number of values; TRUE = correctly recognized exercises; FALSE = wrong recognition of exercise; BBP = barbell bench press; BBSq = barbell back squat; BDL = barbell deadlift

Table 12

Confusion matrix of the exercise recognition task. The number in the matrix indicates number of true exercise recognized as predicted exercise

		<i>predicted</i>								
<i>true</i>	N = 363	BBP	BBSq	BDL	DL	LR	GSq	Sm	TKB	N/A
	BBP	115			3					1
	BBSq		98			2	7	1		13
	BDL	1		115	1				2	5

Notes. N = number of values; BBP = barbell bench press; BBSq = barbell back squat; BDL = barbell deadlift; DL = dumbbell lunges; LR = lateral raises; GSq = Goblet Squat; Sm = Superman; TKB = triceps kickbacks; N/A = no exercise was detected, analyzing screen kept showing

3.3.2 Repetition counting. The overall repetition counting has shown to have an insignificant difference and a moderate positive relationship between the true repetition counting and the recognized repetition counting (*p*-value of 0.06, *r* of 0.40). The results have also shown that there is a significant difference (*p*-value of 0.01) between the true and the recognized repetition counting for the BBP.

Table 13

Repetition counting accuracy of the three exercises

	<i>N</i>	<i>TR_{mean}</i>	<i>RR_{mean}</i>	<i>RMSE</i>	<i>p</i>	<i>r</i>
BBP	118	8.84 ± 2.01	9.44 ± 3.15	1.36 ± 2.16	0.01	0.61
BBSq	108	9.47 ± 1.20	9.31 ± 4.09	2.51 ± 3.08	0.68	0.24
BDL	119	9.41 ± 1.54	9.97 ± 3.80	2.57 ± 2.47	0.09	0.37
total	345	9.23 ± 1.59	9.58 ± 3.67	2.14 ± 2.56	0.06	0.40

Notes. N = number of values; TR = true repetition counting; RR: recognized repetition counting; RMSE = root mean square error; *p* = t-test; *r* = Pearson correlation coefficients

3.3.3 1RM prediction from the smart watch application. Due to the low number of predicted 1RMs, the precision of the prediction was not being calculated.

Table 14

1RM predictions as taken from the app, categorized in attempts, predictions and % of successful attempts

	<i>N</i>	<i>attempts of prediction</i>	<i>predicted</i>	<i>% of successful attempts</i>
BBP	30	30	2	6.7 %
BBSq	30	30	1	3.3 %
BDL	30	30	3	10 %
total	90	90	6	8.9 %

Notes. N = number of values; BBP = barbell bench press; BBSq = barbell back squat; BDL = barbell deadlift

3.3.4 User interface of the app. Here are the two main interfaces of the strength training app from the iPhone, that show common errors and will be used for the discussion.

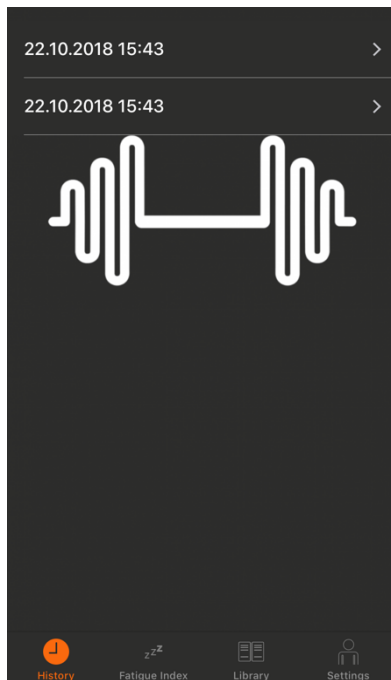


Fig. 12. The first interface of the app after launching it, showing the performed workouts with the date and time.

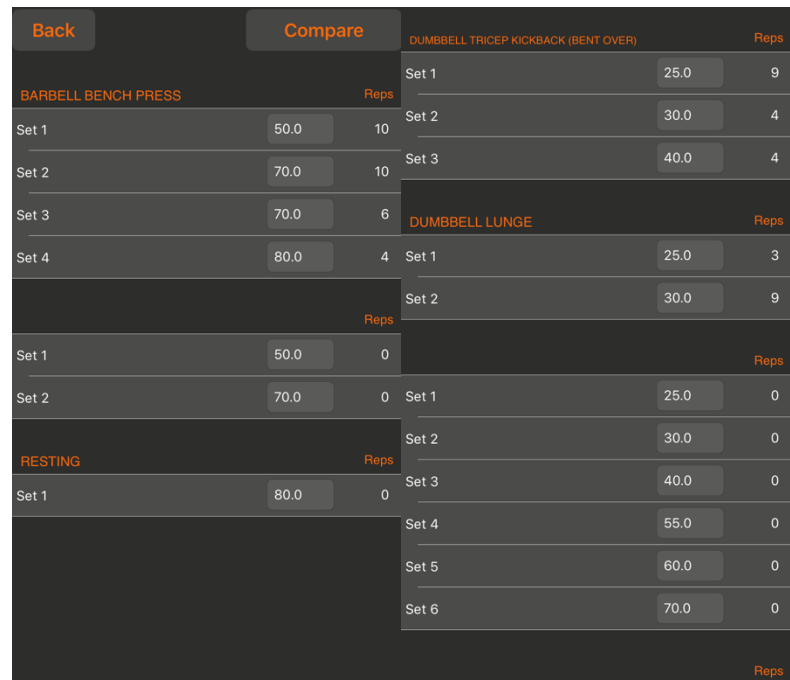


Fig. 13. This is the view of the app upon touching the workout with its closer details showing the performed exercises, the weights used and the repetitions performed.

4 Discussion

The following chapters firstly discuss the results of both aims and gives an overview of the findings. Then, the limitations of the method and the results for this thesis will be pointed out. To conclude this chapter, research and practical implications will be given.

4.1 1RM predictions

The overall results have shown that there is a probability of $p < 0.01$ that the differences between any two 1RM prediction methods are by hazard. This indicates that the differences are significant and not just by coincidence. Only the comparison between the adapted methods of Jovanović and Flanagan (2014) based on load-velocity ($\%1RM = \text{slope}^{V_{Peak}} * MVT + \text{intercept}^{V_{Peak}}$) and the formula of Epley (1985) based on reps-to-fatigue ($\%1RM = \text{weight lifted} * (36 / (37 - \text{No. of reps}))$) for the barbell bench press exercise resulted in a p of 0.29, which is above the significance level of 0.05.

The coefficient of determination (R^2) between the two formulas of Jovanović and Flanagan (2014) and Epley (1985) was 0.9828 for the BBP, 0.8556 for the BBSq and 0.8309 for the BDL. Comparing those results with the other relationships we can also point out that the BBP had the overall best relationships between all three tested relationships, followed by the BBSq and ending with the BDL, which had the coefficient of determination of the lowest score. Furthermore, through guiding our viewpoint from the sum of squares total to the sum of squares error that can be seen in the RMSE value, the same results can be found. The RMSE of the BBP showed an overall smaller distribution of errors with values between 3.49 to 6.95 for all three relationships, compared to 12.15 to 45.48 for the BBSq and 14.90 to 63.09 for the BDL. Those results indicate a tendency towards a usage of Jovanović and Flanagan's (2014) velocity parameter V_{Peak} and MVT for a future app implication. This implies that the user of the app would have to perform each set with maximal velocity. Therefore, other options of 1RM estimation should be integrated into the app, in order to broaden the spectrum of users. As discussed in chapter 1.2.1 mostly power athletes, such a contact sports, throwing events and weightlifters, have a main interest in performing repetitions with a maximal concentric velocity and could therefore get accurate results using this formula. Other more recreationally oriented athletes could still make usage of this feature, but at the same time should have the option in the app to switch to Epley's (1985) reps-to-fatigue formula. This could be included in the app's overview menu, where bodyweight, body height and sex are already successfully integrated.

4.1.1 MVT. As explained in chapter 2.1 the MVT values used for the adapted Jovanović and Flanagan (2014) formula were 0.15 for BBP, 0.25 for BBSq and 0.3 for BDL. Those three values have shown to be the most successful in regards of the relationship to Epley's (1985) formula. Nevertheless, I looked at the collected data for each exercise ($N = 30$) and determined my own MVT values, which resulted in 0.16 for BBP, 0.35 for BBSq and 0.45 for BDL. Especially the MVT of 0.16 ± 0.05 for BBP can be compared with similar results from other authors, such as 0.15 ± 0.03 (Izquierdo et al., 2006; Turner, 2017), 0.16 ± 0.04 (González-Badillo & Sánchez-Medina, 2010) and 0.17 (L. Sánchez-Medina et al., 2014). All these authors share a similar subject group consisting of strength-trained athletes that have a 1RM between 88 and 91. The lower MVT values from the authors summarized in table 2 show an increased experience level of the athletes and also a more specific power oriented athlete group, such as powerlifters with an MVT of 0.10 ± 0.04 (Helms, 2013) and college-aged experienced benchers with an MVT of 0.14 ± 0.04 (Ormsbee et al., 2017). The MVT of 0.35 ± 0.09 for BBSq can only be compared with the results of Zourdos et al. (2016), who had an MVT of 0.34 testing back squats from novice squatters and Pallarés et al. (2014), who had an MVT of 0.37 for paused squats and 0.39 for regular squats using a smith machine. All other authors had smaller MVT values varying from 0.23 to 0.3. Those results would indicate that the tested subject group consisted of mainly novice squatters or that their squatting technique was not the best, whereby, maximal concentric velocity could not be achieved. There was only one source (Helms et al., 2017) that looked at MVT for the BDL and they used experienced powerlifters, which already indicates that their MVT value will most likely not be similar to the MVT of this subject group. Their MVT of 0.14 ± 0.05 was indeed much lower than my MVT of 0.45 ± 0.13 . This big difference can be a result of the contrasting level of sports performances and experience in lifting.

4.2 Detection accuracy of the app

Likewise to its previous testing (Huber, 2017) non-laboratory conditions were used and, nonetheless, the app showed an overall satisfying performance. Unfortunately, not all the sets gave conclusive data, as the smartwatch was sometimes stuck in a loop. Huber talked about similar lag problems that might have been caused by a too slow Apple S1 processor (CPU) of the Apple Watch 1st Generation.

4.2.1 Exercise recognition. The app's algorithm achieved an overall exercise recognition accuracy of 88.4 %. The BBP was the most accurate measurement with low mean %error of -3.5 % followed by the BDL with a mean %error of -7.8 %. The BBSq exercise recognition was the most inaccurate with a high mean %error of -23.5 %, corresponding to almost ¼ of the measurements taken. Comparing those results with the previously concluded findings by Huber, we can see that his exercise recognition accuracy of 96.51 % was much higher. This could be explained through the usage of different exercises in Huber's testings, such as the additionally utilized exercises barbell biceps curl, dumbbell biceps curl with twist and the dumbbell lunches, which performed almost perfect accuracy (1 out of 39 was wrong). Nevertheless, the biggest difference is between the two BBSq accuracies. Huber had a BBSq (N = 16) mean %error of 0.00 % compared to 23.5 % of this thesis (N = 121). On the one hand, this could be explained through the big difference in sample size, but on the other hand, also due to the technical difficulties of BBSq including various lengths of ranges of motion. Furthermore, out of these 23.5 % (N = 23) were 13 sets non-detectable. In other means, the smart-watch had a lag and was not able to process the data properly.

4.2.2 Repetition counting. Even though, the *p*-value of the BBSq and the BDL indicated an insignificant difference, having a look at the RMSE value revealed that the errors self-correct themselves through equaling out positive and negative results and are therefore just as inaccurate as the BBP results.

Comparing those results with the overall mean %error of 0.92 % from Huber, a big difference can be observed. Explanations for this big difference can be the relatively low sample size of Huber (N = 83) compared to this sample size (N = 345), but also the kind of exercise execution in both tests. Huber did not explicitly focus on repetitions with maximal concentric velocity or clear instructions on the execution speed. Therefore, the inaccurate repetition counting could also be due to the rapid concentric movements and non-standardization of the pauses between the eccentric and concentric movements. As Pallarés et al. (2014) suggested, maybe imposing a 2-s pause between the eccentric and concentric phases of each repetition would increase the reliability of isoinertial strength tests. He indicated that «the stop technique resulted in a significantly lower coefficient of variation for the whole load-velocity relationship compared to the standard one» (p. 1165). Maybe through lowering the coefficient of variation in load-velocity data readings by adding a clear instruction to the pauses, the implemented algorithm could execute the repetition counting more clearly and with a bigger precision.

4.2.3 1RM predictions. Transferring the data from the Apple watch to the App on the iPhone caused the most problems and disturbances. Only 8.9 % of attempts were successful and gave a 1RM prediction. The precision of 1RM predictions was due to its low number of predicted 1RMs not being calculated. There were two main issues. The first and more predominant issue was that the transfer of data caused problems with opening the app. Once the icon of the app was touched either nothing happened, or the app started launching and crashed within seconds. After repeated trials, the app on the iPhone had to be reinstalled, which also forced a reinstallation of the app on the Apple watch and in its process lost the collected data from the previous testing. The second issue was that, once the app actually opened, there were repeated workouts and sets, as seen in Fig. 12 and 13, that sometimes showed the wrong weights or did not count any repetitions. Deleting a whole workout or a single set did not cause any problems, but there were issues with changing the weights or the reps of individual sets. Sometimes the changes were possible without having the app lag or even crash, but then caused problems with saving the settings. In those cases, the 1RM predictions for the detected exercises stayed on 0.

4.2.4 User interface. The user interface of the iPhone app was already discussed on the previous chapter showing its issues with the lagging and the repetitive listings. Nonetheless, the overall appearance of the app and its structure was quite user friendly. The four main menus being History, Fatigue Index, Library and Settings were arranged logically and could definitely be operated by a broader public. Overall, the design, the choice of colors and the logo are great and serve as a solid foundation of the app. Nevertheless, it still needs some work and improvements in its data accuracy and data processing till it is ready for publication.

The user experience on the Apple watch was perceived very positively. Once the users got used to the Apple mechanics of touching, scrolling and waiting, the app did not show any major complications. However, there were some minor dissatisfactions that could easily be solved with some tweaks in the coding. Sometimes the display went black (sleep mode) after starting a set or after some repetitions and there was no way to observe the accuracy of the repetition counting and exercise detection. Throughout the testing there was no identifiable pattern of this incident. When asked about the user experience, some users were hoping for haptic feedback when using the Digital Crown, which could be implemented when adding the weights. Others asked for an audible tone when starting the workout, as there was a 3-5 seconds pause between the touching of the start button and the starting of the analyses screen and it was not clear through a visual or audible clue that this process has already started. This caused problems with impatient test subjects, as they repeatedly touched the start button.

4.3 Limitations

Four limitations (method, sample profile, data comparison and app integration) are considered having an effect on generalizing the result and will be discussed in more detail. Not having integrated a direct method for the 1RM estimation for comparisons with the three chosen indirect methods, makes it difficult to determine the real 1RM value. Direct methods for 1RM estimations are, as already thoroughly discussed in chapter 1.1, very time consuming and would have blown up the overall time consumption of this thesis. The same goes to finding willing subjects that voluntarily take their time to repeatedly show up for testings. Nevertheless, having precise 1RM evaluations through applying the direct method would raise the quality of results and should be taken into consideration in future research.

As already described in Table 6 and Table 16 the subjects consisted of a heterogeneous strength trained group that varied from the age of 19 to 41. This group profile was considered as suitable to cover the main target group of the future app users. Nonetheless, making more distinct groups with focuses on power-oriented athletes and a more general recreationally oriented athlete group would maybe be more beneficial.

As the data accuracy of the app could only be compared with one study that based its results on performances by one subject (Huber, 2017) and the sample size was vastly higher, making generally valid statements were hard. Most of the inaccuracies could be explained through the fact, that the previous measurements were based on subject with a predetermined body height. The body height has a big influence on the possible range of motion and, thus, on the detection accuracy of the implemented algorithm. This has largely influenced the exercise analysis and the repetitions counting.

Integrating an adapted version of Jovanović and Flanagan's (2014) formula that uses V_{peak} and MVT would also call for an alternative for exercises that have no known MVT. Therefore, the formula cannot be generalized and needs to be individualized for every exercise.

4.4 Implications

For future research, having a gold standard that relies on a direct method could improve the accuracy of evaluation, especially when compared with different 1RM predictions. An additional goal should be to achieve an exercise detection of over 95 %. An improvement should also be made to the velocity reading through weight displacement. Particularly if a successful integration of the 1RM prediction formula using the velocity-based parameters V_{peak} and MVT is aimed for. Furthermore, an improved spatial recognition through recognized and ac-

cepted variation of exercise execution has to be achieved. The variability of how the watch can be worn (integration of right and left) should be implemented.

For practice, there are three focus points that can be discussed. First of all, an integration of a haptic feedback could facilitate the user's understanding of the application's usage. This can be achieved through adding acoustic tones when pressing buttons (start and stop button) and vibrations when using the Digital Crown. Secondly, an integration of a rest period timer, which starts automatically after the last repetition or when pressing the stop button, would help the user to track the intervals of each set more precisely. Lastly, integrating individual exercise calibration for MVT calculations would improve the accuracy of the 1RM predictions.

5 Conclusion

The findings of this thesis have shown that the adapted formula of Jovanović and Flanagan (2014) and Epley (1985) had the best correlations of 1RM predictions in submaximal load (60 – 80 %) in all three exercises (barbell bench press, barbell back squat and barbell deadlift), whereas, the barbell bench press performed the highest overall. The results propose an implementation of the parameters V_{peak} and MVT used by Jovanović and Flanagan (2014). Hereby, it is important to draw the attention to the fact that using those parameters asks for performances in maximal concentric velocity and that the user should be aware of that. Athletes that do not focus on power output, should therefore have the option through changing the preferred settings in the application to Epley's (1985) Reps-to-Fatigue formula that uses the parameters repetition and load. A setting like 1) Performance, 2) Hobby could be aimed for. At the same time, an integration of a velocity-based parameter also asks for an improvement in the Apple watch application's data acquisition of velocity measurements through weight displacement.

The validation of the application's functions indicated a high accuracy (88.4 %) of the exercise recognition algorithm provided by FocusMotion. It also showed an insignificant correlation ($p = 0.06$) between the true and the recognized repetition counting. The implemented 1RM estimation did not give enough data to make a proper calculation of results and was, therefore, not further analyzed.

To improve the smart watch application, future work has to be put into updating the detection method of weight displacement of the Apple Watch, lowering the needed volume of data transmission to eliminate lags the Apple Watch and the iPhone application and to enhance the overall user experience integrating haptic feedback.

Once those improvements are made, the app will be showing efficient accuracy and usability as an effective workout assistant device, resistance training would be made available to a broader public, overall health would be promoted and the app would be able to encourage a mitigation of progression or even a reversion of existing chronic diseases.

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Appendix

List of abbreviations

Here is a list of used terms to facilitate and clarify their usage.

Table 15

List of used terms for this paper with corresponding meaning and explanation

Term	Meaning	Explanation
IRM	one repetition maximum	An established measure of muscular strength; it is defined as the value of resistance against which a given movement can be performed only once (Niewiadomski et al., 2008)
BBP	barbell bench press	
BDL	barbell deadlift	
BBSq	barbell back squat	
kg	kilograms	measurement of mass in the International System of Units (SI)
lbs	pounds	weight in kg * 2.2046; measurement of mass used in the imperial system
LOC	level of confidence	
m·s⁻¹	meters per second	measurement of speed in the International System of Units (SI)
MPV	mean propulsive velocity	Average velocity from the start of the concentric phase until the acceleration of the bar is lower than gravity (García-Ramos, Pestaña-Melero, Pérez-Castilla, Rojas, & Haff, 2017)
MV	mean Velocity	Mean velocity recorded across all time intervals of a movement (Jovanović & Flanagan, 2014); Average velocity from the start of a concentric phase until the bar reaches the maximum height (García-Ramos et al., 2017)
Mean5	mean velocity 5	Mean velocity recorded during the first 5 repetition of a movement.
PV	peak velocity	Maximum instantaneous velocity value reached during the concentric phase (García-Ramos et al., 2017)
PBT	percentage based training	
R²	coefficient of determination	
SA	subjective autoregulation	
SI	International System of Units	SI stands for the French <i>système internationale</i> and includes seven base units
VBT	velocity based training	The use of velocity measurements for determination of training load, volume, frequency and other factors (Jovanović & Flanagan, 2014)

Subject group

Table 16

Detailed overview of subject group with corresponding sex, age, height, weight (in kg and lbs), BMI and years of training experience

Subject	Sex	Age	Height (m)	Weight (kg)	Weight (lbs)	BMI	Years of training experience
1	m	33	1.68	70	154.3	24.8	5
2	m	19	1.9	116	255.7	32.1	2
3	m	25	1.79	95	209.4	29.6	5
4	f	29	1.6	59	130.1	23.0	3
5	m	34	1.82	80	176.4	24.2	15
6	m	40	1.73	62	136.7	20.7	5
7	m	34	1.73	90	198.4	30.1	17
8	m	35	1.85	93	205.0	27.2	10
9	m	24	1.8	95	209.4	29.3	9
10	f	23	1.65	60	132.3	22.0	6
11	f	35	1.63	55	121.3	20.7	2
12	f	26	1.68	61	134.5	21.6	1
13	m	31	1.78	87	191.8	27.5	5
14	m	29	1.81	74	163.1	22.6	2
15	m	26	1.72	75	165.3	25.4	6
16	f	24	1.58	54	119.0	21.6	5
17	f	27	1.63	53	116.8	19.9	2
18	m	24	1.86	80	176.4	23.1	2
19	f	36	1.84	78	172.0	23.0	2.5
20	f	24	1.73	65	143.3	21.7	3
21	f	41	1.64	53	116.8	19.7	0.5
22	f	28	1.74	65	143.3	21.5	1
23	f	32	1.61	53	116.8	20.4	5
24	m	20	1.8	83	183.0	25.6	10
25	f	26	1.68	66	145.5	23.4	5
26	f	23	1.65	68	149.9	25.0	3
27	f	29	1.65	67	147.7	24.6	5
28	f	35	1.7	56	123.5	19.4	3
29	f	20	1.77	77	169.8	24.6	2.5
30	m	20	1.73	85	187.4	28.4	2

Overview of 1RM predictions

I. Barbell bench press

Table 17

Barbell bench press 1RM predictions of the three methods Epley (1985), Jovanović and Flanagan (2014) and Sayers et al (2018) and their RMSE

Subject	1RM Epley	1RM Jovanovic	1RM Sayers	RMSE E_M	RMSE E_S	RMSE M_S
1	70.92	64.99	72.46	5.93	1.54	7.46
2	84.00	86.75	96.69	2.75	12.69	9.94
3	118.25	118.80	123.62	0.55	5.37	4.83
4	45.33	51.11	52.07	5.77	6.74	0.97
5	120.00	111.08	124.20	8.92	4.20	13.12
6	64.17	64.68	66.98	0.51	2.81	2.30
7	110.83	113.48	115.81	2.64	4.98	2.34
8	128.33	118.63	140.54	9.70	12.21	21.91
9	138.00	149.98	152.50	11.98	14.50	2.52
10	45.00	50.06	51.58	5.06	6.58	1.52
11	30.83	36.53	40.15	5.69	9.31	3.62
12	32.08	42.08	42.02	9.99	9.94	0.06
13	93.50	93.38	99.61	0.12	6.11	6.23
14	65.17	66.89	68.75	1.72	3.58	1.86
15	110.50	112.36	119.19	1.86	8.69	6.83
16	40.00	43.54	45.15	3.54	5.15	1.61
17	49.33	51.78	52.70	2.44	3.36	0.92
18	84.58	80.19	80.31	4.39	4.27	0.12
19	36.00	39.44	42.38	3.44	6.38	2.94
20	39.00	38.26	19.56	0.74	19.44	18.71
21	37.00	37.51	40.73	0.51	3.73	3.23
22	40.00	39.18	42.28	0.82	2.28	3.10
23	53.33	49.53	58.52	3.81	5.19	9.00
24	135.67	135.62	145.33	0.04	9.66	9.70
25	46.67	51.54	63.41	4.87	16.75	11.88
26	55.50	56.28	59.47	0.78	3.97	3.18
27	38.00	36.99	38.58	1.01	0.58	1.58
28	27.00	29.05	34.08	2.05	7.08	5.03
29	49.50	48.95	52.96	0.55	3.46	4.00
30	101.33	98.97	109.29	2.37	7.95	10.32

II. Barbell back squat

Table 18

Barbell back squat 1RM predictions of the three methods Epley (1985), Jovanović and Flanagan (2014) and Sayers et al. (2018) and their RMSE

<i>Subject</i>	<i>1RM Epley</i>	<i>1RM Jovanović</i>	<i>1RM Sayers</i>	<i>RMSE E M</i>	<i>RMSE E S</i>	<i>RMSE M S</i>
1	106.67	118.87	135.51	12.21	28.84	16.63
2	133.33	172.74	228.15	39.41	94.81	55.41
3	141.83	136.31	195.13	5.52	53.30	58.82
4	100.00	100.33	118.39	0.33	18.39	18.07
5	120.00	123.41	138.85	3.41	18.85	15.44
6	86.67	105.23	171.09	18.56	84.42	65.86
7	172.67	190.22	220.18	17.56	47.51	29.96
8	140.00	197.17	197.16	57.17	57.16	0.02
9	198.00	199.49	241.93	1.49	43.93	42.45
10	73.33	84.84	119.20	11.51	45.87	34.36
11	61.25	58.31	81.73	2.94	20.48	23.42
12	69.67	112.00	174.08	42.33	104.41	62.08
13	126.67	134.12	243.44	7.45	116.77	109.32
14	101.33	126.14	135.22	24.81	33.89	9.08
15	133.33	134.32	150.27	0.99	16.94	15.95
16	82.33	83.30	113.09	0.96	30.75	29.79
17	113.33	115.78	147.16	2.45	33.82	31.37
18	126.67	173.31	243.30	46.64	116.63	69.99
19	80.17	100.22	157.00	20.05	76.83	56.78
20	84.50	75.78	83.34	8.72	1.16	7.57
21	80.00	88.68	127.67	8.68	47.67	39.00
22	73.33	77.44	104.07	4.11	30.74	26.63
23	83.33	87.31	122.64	3.98	39.30	35.32
24	139.33	152.60	205.64	13.27	66.31	53.04
25	75.83	77.40	89.23	1.56	13.39	11.83
26	110.00	110.34	143.21	0.34	33.21	32.87
27	73.33	70.76	92.34	2.58	19.01	21.59
28	40.08	41.74	47.09	1.66	7.01	5.35
29	71.50	72.13	82.82	0.63	11.32	10.69
30	156.67	159.75	208.44	3.08	51.77	48.69

III. Barbell deadlift

Table 19

Barbell deadlift 1RM predictions of the three methods Epley (1985), Jovanović and Flanagan (2014) and Sayers et al. (2018) and their RMSE

<i>Subject</i>	<i>1RM Epley</i>	<i>1RM Jovanović</i>	<i>1RM Sayers</i>	<i>RMSE E M</i>	<i>RMSE E S</i>	<i>RMSE M S</i>
1	104.00	126.91	161.12	22.91	57.12	34.20
2	148.00	131.54	160.75	16.46	12.75	29.21
3	163.33	200.00	201.37	36.67	38.03	1.37
4	104.83	101.64	129.76	3.19	24.92	28.12
5	152.00	165.70	256.26	13.70	104.26	90.56
6	93.33	97.23	186.12	3.89	92.79	88.89
7	183.67	254.89	438.70	71.23	255.03	183.81
8	206.67	213.69	272.10	7.02	65.44	58.42
9	233.33	217.31	255.61	16.02	22.28	38.30
10	60.00	105.85	214.20	45.85	154.20	108.35
11	72.00	66.68	78.45	5.32	6.45	11.76
12	75.83	101.25	145.89	25.42	70.05	44.63
13	118.25	127.47	161.59	9.22	43.34	34.12
14	120.00	151.58	234.78	31.58	114.78	83.20
15	153.33	150.92	195.46	2.42	42.12	44.54
16	114.00	105.15	163.27	8.85	49.27	58.12
17	120.00	124.07	205.38	4.07	85.38	81.32
18	120.00	141.83	175.34	21.83	55.34	33.51
19	82.33	104.03	176.54	21.70	94.20	72.50
20	73.33	82.66	108.05	9.33	34.71	25.39
21	79.33	84.22	106.63	4.89	27.29	22.40
22	86.67	91.37	134.18	4.71	47.51	42.81
23	100.00	98.24	185.00	1.76	85.00	86.76
24	160.00	144.53	221.26	15.47	61.26	76.73
25	86.67	102.41	124.23	15.75	37.56	21.82
26	123.33	124.98	190.85	1.65	67.52	65.87
27	73.33	56.76	64.47	16.58	8.86	7.71
28	53.83	56.76	64.47	2.92	10.64	7.71
29	106.67	103.18	139.26	3.49	32.59	36.08
30	160.00	163.00	251.98	3.00	91.98	88.98